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Projecting the urban energy demand for Indiana, USA, in 2050 and 2080

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Abstract

Energy use is one of the largest drivers of climate change, but the large share of energy used for space heating and cooling is also driven by climate change. Demand for energy, particularly cooling, is important for long-range infrastructure planning. Urban areas represent a very small proportion of total land, but usually consume the majority of energy. In this work, statistical, top-down approaches are used to model residential and commercial urban energy demand changes in Indiana, a state in the Midwest region of the USA, in 2050 and 2080 under the climate change scenarios of RCP 4.5 and 8.5. By modeling energy demand changes in urban areas in Indiana, we can project the majority of energy demand while placing it in a spatial perspective that is missing from the statewide estimates. Two time periods are used to give an intuitive time stamp and temporal perspective. Results indicate that Indiana's northernmost cities are expected to show significantly increased residential cooling demand due to climate change by 2080. Indianapolis represents an increasing share of total urban commercial and residential energy use over the next 60 years. Transportation is expected to represent a larger share of energy use as heating demand declines under climate change scenarios.

Keywords Urban, Energy, Climate change

1 Introduction

Cities are home to a majority of the world's population but make up less than 3% of terrestrial land (Seto et al. 2015), and possibly as little as 0.51% (Schneider et al. 2009). Accordingly, the International Energy Agency posited that 64% of global primary energy use took place in cities in 2013 (Masanet et al. 2016). This trend has also been found in the USA (Parshall et al. 2010), which is important both for forecasting future energy use and targeting policies. While this work is focused on the consequences of climate change in terms of energy use, energy use is also one of the largest contributors to greenhouse gas emissions, representing a feedback loop. Particularly after the exit of the USA from the Paris Agreement, increasing attention has been placed on the potential for more distributed action by the more than 300 "climate mayors," who have affirmed their commitment to meet international goals for climate change mitigation (Watts 2017).

As part of the Indiana Climate Change Impacts Assessment (IN CCIA), high-resolution forecasts were made available for Indiana for the time period up to 2100 for two climate change scenarios:

representative concentration pathway (RCP) 4.5 and RCP 8.5. The numbers in the scenario names refer to the amount of radiative forcing present in the atmosphere in 2100 in W/m2. The principal tasks of the energy working group for the IN CCIA were to project the effects of climate change on statewide energy consumption, and estimate the effects of policies on the supply mixture (Raymond et al. 2019; this issue). An understanding of the energy demand changes spatially across the state, specifically centered in urban areas, was desirable in order to develop an actionable plan to meet the changing energy demand in response to climate change. According to the US Census Bureau's classification of urban areas, Indiana is home to 15 cities or parts of cities (US Census Bureau 2012a), which contain 77% of the state's population according to 2010 census numbers (5,036,573 of 6,483,802 inhabitants) (US Census Bureau 2012a). Hence, in this work, we focused more narrowly on Indiana's urban areas and their energy demand, specifically considering how residential and commercial urban energy consumption is likely to shift due to climate change.

The RCP 4.5 scenario assumes the adoption of carbon pricing and other mitigation policies, with emissions peaking near 2040 and stabilizing near 525 ppm CO_2 and 650 ppm CO_2 equivalents (Thomson et al. 2011). RCP 8.5 is sometimes referred to as a "business as usual" or "baseline" scenario. It assumes that no global greenhouse gas emission mitigation strategy is adopted. Instead, the world population continues growing, reaching 12 billion by 2100, with low levels of economic growth and technological innovation. Thus, fossil fuels present a more economical choice than renewables, leading to a high level of use for coal (cleaner coal technologies like gasification are employed over time) and nontraditional petroleum products (Riahi et al. 2011). Some criticism of RCP 8.5 as a reference case has emerged since estimates of coal's availability may prevent its use as a "backstop" fuel in such a scenario (Ritchie and Dowlatabadi 2017). Still, the RCP 8.5 scenario reads as familiar, since it assumes the use primarily of fossil fuels for energy provision while in the policy sphere a higher priority is placed on air pollution than climate change mitigation. Recently in the USA there has been much talk of reviving interest in "clean coal." Indiana, the site of our study, has high levels of coal production (8th among states in the USA as of 2015 US Energy Information Administration 2017b), and receives the majority (> 70% as of Nov 2017 US Energy Information Administration 2017b) of electricity from coal power generation plants—Indiana is currently the third largest consumer state of coal in the USA, and recently opened a clean coal electricity generation plant (in Edwardsport), so RCP 8.5 indeed presents a relevant storyline here.

In order to estimate urban energy demand, it is necessary to understand the driving reasons behind its changes. Energy demand change is a complex phenomenon with several driving variables that may change simultaneously, including increased urbanization, population growth, population density change and income increases. The specific questions driving our work were: how a warmer climate would affect urban energy use? What is the time frame for the changes, i.e., will most changes happen soon, or later? Where might the largest changes occur in Indiana's cities? How much certainty is there about these estimates, and what is needed to improve on this?

To address these research questions, two time periods (2050 and 2080) were examined and compared with 2015 estimates. Energy demand for heating, electricity, and transportation in Indiana's urban areas was estimated by two methodologies, one developed in Singh and Kennedy (2015) and the other from Kennedy et al. (2015). Residential cooling was estimated by a method developed in McNeil and Letschert (2008) and refined in Isaac and van Vuuren (2009).

These estimates provide greater spatial and temporal resolution than the energy demand forecasts published by Raymond et al. (2019; this issue), and may thus be more relevant for individuals and stakeholders. The methods developed earlier for urban-scale energy consumption and cooling energy demand have not been applied to the state of Indiana using the downscaled climate projections developed recently by Hamlet et al. (2019; this issue). Hence, this work uses the methods developed earlier in Singh and Kennedy (2015) and McNeil and Letschert (2008) to provide projections of energy demand for cities in Indiana under various climate change projections.

2 Background: modeling urban energy consumption

A robust literature seeks to predict and model energy consumption, including in urban areas. On a national scale in the USA, the Energy Information Administration (EIA) makes detailed forecasts according to multiple scenarios on a national level. MARKAL (Fishbone and Abilock 1981) is frequently used at national scale to model supply, and an Indianaspecific version of MARKAL was used in Raymond et al. (2019; this issue). The long-range energy alternatives planning (LEAP) system (Heaps 2016) is also frequently used at national scale. Still, models applicable to a range of places at a higher spatial resolution (subnational, below state level) are lacking. In the USA, two national studies have focused on urban energy demand estimation. The Vulcan model (Gurney et al. 2009) was used for a study of US urban areas by Parshall et al. (2010). Vulcan has not been updated after 2002, however, and the work in Parshall et al. (2010) could not be disaggregated to focus on individual cities.

Brown and Logan (2008) purchased proprietary data for use in their study of residential electricity, transportation, and fuel consumption in the 100 largest US cities by population. They also performed statistical analysis to find significant predictors for residential carbon footprints. The most recent data source was 2005. Interestingly, Indianapolis had the 3rd highest per capita carbon footprint for residential electricity and fuel use in 2000 and 4th highest in 2005. When electricity alone was considered, Indianapolis was 7th in 2000 and 5th in 2005 (Brown and Logan 2008).

At global scale, Singh and Kennedy sought to model urban energy demand change in response to climate change based on predictive variables (Singh and Kennedy 2015), with a statistical methodology that is adaptable to any group of cities. The model was developed based on empirical data on energy consumption at city scale along with the estimates of predictor variables calculated at same city scale. The modeling focused on urban energy demand in three major categories: transportation, electricity, and heating. Both electricity and heating were found to be dependent on temperature accounted by the variable of Heating Degree Days (HDD), thus directly effected by changing climate. In this work, the cooling energy demand was accounted for in electricity consumption. This model was applied globally for 3646 cities after testing for extrapolations using statistical approach of leverage to caution for any projection errors.

Kennedy et al. (2015) classified material flows more broadly in “megacities,” along with including predictive characteristics of variables for energy demand in urban areas, similar to Singh and Kennedy (2015). This work also looked at electricity, heating, and transportation, but only heating was tied to temperature, perhaps due to the nature of “megacities” where electricity was mostly driven by urban form and GDP, which were highly correlated. However, both works independently confirmed temperature to be a major driver of heating energy consumption in urban areas.

Cooling energy modeling

The contemporaneous trends of development and climate change have led to interest in projecting changes in global adoption of space cooling technologies. In many of the hottest places, people have historically had little access to air conditioning, but this may change in the coming years. Whether, where, and how quickly this might change have been the focus of several studies (Sivak 2009; Isaac and van Vuuren 2009; McNeil and Letschert 2008; Davis and Gertler 2015). Cooling is particularly important because in many areas it has a large impact on the peak load despite it's relatively small proportion of overall energy use.

Cooling degree days (CDD) has been used as predictor variable for cooling energy estimation since it captures the effective number of days when cooling is required with respect to a baseline temperature that represents thermal comfort for people. Hence, CDD is a good proxy variable for quantifying cooling energy demand as in the model by Isaac and van Vuuren (2009). Sivak (2009) found that many of the fastest growing cities had very high CDD, indicating a high potential for future cooling demand in cities in the developing world.
Likewise McNeil and Letschert (2008) looked at the emerging adoption of air conditioning in the residential sector of developing countries. Isaac and van Vuuren (2009) expanded their approach to a global scale for inclusion in the TIMER model. Air conditioners are much more energy intensive (i.e., to achieve the goal of space cooling, air conditioners use a large amount of energy) and expensive than other cooling technologies (e.g., fans). Their energy intensity makes their usage a good proxy for space cooling energy use. McNeil and Letschert noted that ownership of air conditioners is strongly correlated with income, following an S-shaped diffusion curve (McNeil and Letschert 2008), so that once a certain threshold income level is reached (in Isaac and van Vuuren 2009, it is around $10,000 per capita), ownership rises rapidly. This income threshold has been met in the USA, usually considered one of the areas with the highest adoption of air conditioners. In the USA, 87% of homes have air conditioning as of 2015, and 65% of homes have central air (US Energy Information Administration 2017a).

Saturation of air conditioners in a given area is also highly dependent on climate (McNeil and Letschert 2008; Sailor and Pavlova 2003) and the interaction of climate and income is even more important (Davis and Gertler 2015). Sailor and Pavlova show a logarithmic type curve for the climate effect, since in cooler climates people are unlikely to purchase air conditioners, but in hot climates the saturation is near unity (Sailor and Pavlova 2003). Once air conditioners are available in a household, their usage is highly correlated with climate, with strong increases shown when it is very hot. Davis and Gertler showed in their study of Mexican households that each day with temperatures over 90 ◦F (32.2 ◦C) increased monthly electricity usage by 3.2% (Davis and Gertler 2015). This certainly implies that as climate change results in higher temperatures in certain regions, it will have a direct impact on higher energy demand.

We could not find a model for cooling energy estimation in the commercial sector that could be used at urban scale for the needed projections. Recently in the USA, work by Lokhandwala and Nateghi (2018) analyzed data from the Commercial Buildings Energy Consumption Survey (CBECS) to determine the variables with predictive capability for commercial cooling load. They note the wide agreement that building area is a determining variable, and look at energy use intensity (kWh/m2), showing that while in the past (2003) (Lokhandwala and Nateghi 2018) and prior (Sailor and Mu˜noz 1997) CDD was the most predictive variable, principal building activity now surpasses CDD as a predictor. They also note that the predictive capability of CDD has decreased with respect to energy use intensity, most likely due to improvements in efficiency. Still they note that with those improvements, cooling energy use intensity has not decreased.

As part of the IN CCIA project, Nateghi and Mukherjee (2017) developed a framework for including climate change effects in energy demand estimates. They estimated an increase in commercial demand for space cooling in Indiana in the same study period, but a decrease in residential demand for space cooling. Their work, however, does not address the spatial variability below the state level, i.e., at urban scale. Hence, our work particularly focuses on filling the gap at city scale.

3 Methodology for energy demand change at urban scale

3.1 Heating, electricity, and transportation projections

As mentioned above, Singh and Kennedy (2015) (S-K) and Kennedy et al. (2015) (K-M) both published regression models that can be used for estimation of transportation, electricity and heating energy demand. The models were developed using a regression-based approach that tested the relationship of explanatory variables such as gross domestic product (GDP), CDD, HDD, population density, and inverse population density with empirical data on energy consumption in a group of world cities. Tables 1 and 2 show the variables proven to be significant predictors along with parameters and regression coefficients for energy estimation in each category for each model. Although these models were developed independently using two different datasets, they showed similar significant predictor variables for each category of energy providing confidence in using this methodology for the forecast of energy demand in urban areas.

Table 1 Singh Kennedy (S-K) model (Singh and Kennedy 2015) for urban energy estimation

	Heating degree days	Inverse population density (ha/cap)
Heating* (GJ/cap)	0.014725	–
Electricity* (MWh/cap)	0.000994	144.7
Transportation (GJ/cap)	–	1374.9

For heating demand, only the heating degree days is a significant variable. For electricity, both heating degree days and inverse population density are significant. For transportation, only inverse population density is significant. Inverse population density refers to urban area per capita
*Adjusted from published model as described in Section 3.1

Table 2 Kennedy Megacities (K-M) model for Urban Energy Estimation

	Heating degree days	Inverse population density (km^2/cap)
Heating (GJ/cap)	0.02	57,722
Electricity (MWh/cap)	–	21,614
Transportation (GJ/cap)	–	92,858

Full details can be found in Kennedy et al. (2015)

Full methodologies as well as datasets for deriving the two regressions are discussed in the source papers. The S-K dataset included cities from all over the world with varying population sizes, densities, and stages of development (Singh and Kennedy 2015). The K-M model set had 27 cities with a wider geographic range but included only “megacities,” the largest cities in terms of population size in the world (Kennedy et al. 2015). For this reason, the K-M model is used here to provide a benchmark for the total projections for heating, electricity, and transport.

The S-K model was slightly modified in this work. Since our focus is on the commercial and residential sectors, we excluded a proportion of the heating energy from the dataset based on assumptions of the relative contribution of industry in heating energy demand in those cities. The coefficients included here in Table 1 reflect the adjustments for the exclusion of industrial heating. For the electricity modeling, we combined the datasets from the original work in Singh and Kennedy (2015) and Kennedy et al. (2015), using the S-K data in the case of duplicate cities. We also added electricity usage from Indianapolis, in order to have a more robust dataset with a higher variability in urban form. The source data for the modified regressions in the S-K model used are available in Tables 1 and 2 of the SI.

To use these models, data for density were required. HDD and CDD were required for all cities, which were calculated based on temperature data from the climate group and GISbased methodology proposed in Singh and Kennedy (2015). Further, population data was necessary in order to calculate total energy consumption in each category for all cities. The data collection and calculations for HDD and CDD are discussed in Section 3.3.

3.2 Cooling

Residential cooling estimation

A separate estimation for per capita cooling energy consumption was made based on models developed by McNeil and Letschert (2008) and Isaac and van Vuuren (2009). Cooling consumption cannot be directly calculated from the regression models described above, mainly because the data used for development of regression models aggregated space cooling energy requirements as simply part of electricity consumption. Cooling makes up a relatively small component of energy use (mainly electricity). Nevertheless, the question of whether increased cooling energy use will outpace declines in heating demand has generated much study (see, for example, Dirks et al. 2015; Wang and Chen 2014).

The model used here is based on statistical analysis examining both extensive and intensive behavior related to the use of space cooling equipment. The decision to purchase air conditioning units is a long-term or extensive-type choice. People run the air conditioners more or less in a given year (intensive) based on current weather conditions. Hence, the total energy consumption in this model is a function of both total amount of equipment present and the usage of the cooling equipment.

The total per capita urban cooling energy demand in this model is calculated by Eq. 1, which is from Isaac and van Vuuren (2009) but in a per capita format:

$$T = \frac{P}{h} \times \frac{\mathrm{UEC}}{\mathrm{EE}} \qquad (1)$$

In Eq. 1, *T* is the total per capita cooling energy use (kWh/capita), *h* is the household size [people/household], *P* is penetration (%) (the extensive variable—taking into account the proportion of households that own air conditioners), UEC is the unit energy consumption (kWh/household/year) (usage—the intensive variable indicating how often people use their air conditioners), and EE is the efficiency factor (%). Since UEC depends on CDD (Cooling Degree Days) and GDP per household, i.e., income (*I*) (see Eq. 2), the per capita energy consumption depends on both on climate and income change. The UEC model (Eq. 2) was developed by Isaac and van Vuuren, who ran a linear regression on 37 data points to estimate the usage variable, UEC against the explanatory variables of income (*I*) and CDD (Isaac and van Vuuren 2009). The maximum value allowed is 3500 kWh/year following McNeil et al. (2008).

$$\mathrm{UEC} = \mathrm{CDD} \times (0.865 \times \ln(I) - 6.04) \quad (2)$$

In Eq. 2, I is income, approximated by GDP per household. Next, we assume that penetration in the USA depends only on climate (CDD) (3) as in the original model. Logically, this is true since investment in cooling equipment is driven by the general weather of region; hence, households in warm weather (with higher CDD) are more likely to purchase cooling equipments as captured by Eq. 3 from McNeil and Letschert (2008).

$$P = 1 - 0.949 \times e^{-0.00187 \times \mathrm{CDD}} \quad (3)$$

We present results assuming no efficiency gains as well as results based on a forecast of cooling technology improvement (seasonally averaged COP values—variable EE in Eq. 1). For 2015 we use a COP value of 3.35, a weighted average of the efficiency values based on cooling stock in US residences from table 22 of the 2017 Annual Energy Outlook (Administration UEI 2017). This has been revised from the higher value of 3.81 (given as a 2020 value in Iyer et al. 2017) used in Raymond et al. (2019; this issue) since we were able to calculate this more accurate value for 2015. We estimate expected efficiency gains in cooling technology by interpolating from predicted efficiency increases in the cooling sector through 2100 given by Eq. 4, where y is the year:

$$\mathrm{EE} = -0.0003y^2 + 1.05y - 1092.6 \quad (4)$$

This equation was found by plotting the values of 2.4 for 2000, 3.2 for 2020, and 4.39 for 2100 which follow a polynomial improvement given by the Pacific Northwest National Laboratory (Rong et al. 2007). These efficiency values for 2050 and 2080 of 4.02 (the Annual Energy Outlook Administration UEI 2018 gives a weighted average value of 4.026 for 2050) and 4.39 respectively are included in Eq. 1 following the approach used by Isaac and van Vuuren (2009).

Since no city-level data or estimates of energy use are available, the models were run to create baseline estimates for 2015 to be used as reference year. We used the projectedchanges in CDD for 15 Indiana cities over time, relying on the estimates by the climategroup in this issue (Hamlet et al. 2019; this issue), as the basis for our projections. We alsomade assumptions about income as described below in Section 3.3.

3.3 Data collection

Geographical coverage

The largest city in Indiana is Indianapolis, the capital, whose population was estimated at 2,000,400 in 2015. Indiana is located in the Midwest region of the USA, and for the EIA it is in the East North Central region of the Midwest. It can be split into a southern portion that falls in the “mixed-humid” region (according to the Building America Climate Regions), and the northern part of the state which lies in the “cold” region. The northwest corner of the state includes Gary, which is part of the Chicago metropolitan area. Indiana is bordered to the north by Lake Michigan and Michigan. To the west it borders Illinois, to the south Kentucky, and to the east Ohio. The cities included in this work range in latitude from Michigan City-La Porte, the northernmost city with latitude 41.7, to Evansville, with latitude 38.0. The list of Indiana’s 15 cities is provided in Table 3.

Population

For these urban areas, population projections in 5-year increments extending to 2050 were available in STATS Indiana (2012). Since no population projections were available for 2080, we extended the population numbers to 2080 for each city based on its growth rate from 2045 to 2050, assuming the annual growth rate for the period of 30 years. The population estimates for each city at each point in the study time period are shown in Table 3.

Area and inverse population density

Population density was calculated separately. Where the urban agglomeration's population resided principally outside of Indiana's borders (Cincinnati-Middletown, Louisville-Jefferson and Gary Division), density data from Angel et al. (2012) were used. For other cities the land area for the named components of each city (i.e., Indianapolis and Carmel cities proper) from county and township level census data (US Census Bureau 2012b) was summed to perform the calculations for 2010. The population density was projected forward assuming a 1% yearly decline attributed to the phenomenon of urban sprawling.

Table 3 Cities studied with population figures as used for 2015, 2050, and 2080

City	2015	2050	2080
Bloomington	166,210	198,766	224,365
Cincinnati*	42,063	47,352	45,471
Columbus	79,194	88,112	93,421
Elkhart-Goshen	204,959	248,764	286,441
Evansville*	272,443	292,128	297,881
Fort Wayne	429,967	497,948	544,459
Gary	723,879	778,362	801,495
Indianapolis	2,000,400	2,584,097	3,018,845
Kokomo	82,029	70,080	59,267
Lafayette	211,029	251,032	278,182
Louisville*	287,666	330,988	353,713
Michigan City-LaPorte	112,111	106,949	99,697
Muncie	117,220	109,859	103,194
South Bend-Mishawaka*	268,533	274,940	276,554
Terre Haute	173,132	166,141	157,087

Indianapolis, the largest city, is forecast to increase significantly in population over this period
*Indiana portion of larger metropolitan area

Temperatures

As part of the IN CCIA project, temperature projections were made based on 31 global climate models, from which 10 were selected to best capture the range of results. The values were statistically downscaled to 1/16◦ resolution, approximately 5 by 7 km, for the RCP 4.5 and 8.5 scenarios based on the Coupled Model Intercomparison Project, Phase 5 (CMIP5) (Hamlet et al. 2019; this issue). High and low daily temperatures from three time periods were modeled: 2011–2040, 2041–2070, and 2071–2100. For this work we took an average for each time period to represent the 3 years of 2015, 2050, and 2080.

Note that since these forecasts were not developed specifically for use at urban scale, the urban heat island effect may not be fully shown. Using latitude and longitude, the distance from cities was calculated using the great circle distance method (see description in Singh and Kennedy 2015), and temperatures recorded in any spot less than 10 miles from the city's latitude and longitude were averaged to compute maximum temperature (*t*max) and minimum temperature (*t*min) values for the city. Table 4 shows the temperature increases by 2080 for the cities studied under both scenarios. Highlighted cities as well as Fort Wayne all sit above 41◦ latitude, so represent the northernmost cities.

For RCP 8.5, by 2050 minimum temperatures are projected to rise by 1.21 (Apr and Nov) to 2.08 ◦C on average in the cities studied. Maximum temperatures increase on average 2◦ or higher for Jul–October, with the highest increases seen in August, where some cities see an increase of more than 3◦ (Bloomington and Cincinnati are at 3 even, Columbus and Kokomo are over 3◦). The 4 northernmost cities see above average minimum temperature rise in the winter (Dec–Feb), but not during the rest of the year.

By 2080 average minimum temperatures are projected to rise by between 2.87 and 4.7◦ in the cities studied. In all time periods and scenarios except Dec–Jan–Feb in RCP 4.5, the maximum temperatures increase more than the minimum temperatures. In winter the northernmost cities see the highest increase in minimum temperature. The increase in maximum temperatures is more pronounced, with average increases ranging from 3.23◦ in April to 5.92◦ in August.

City	Temperature Increase in °C 2015–2080															
	Dec-Jan-Feb				Mar-Apr-May				Jun-Jul-Aug				Sep-Oct-Nov			
	RCP 4.5		RCP 8.5		RCP 4.5		RCP 8.5		RCP 4.5		RCP 8.5		RCP 4.5		RCP 8.5	
	h	l	h	l	h	l	h	l	h	l	h	l	h	l	h	l
Bloomington	1.63	1.61	3.27	3.07	1.40	1.32	3.30	3.05	2.21	1.72	**5.24**	**4.26**	1.75	1.44	**4.55**	**4.07**
Cincinnati	1.61	1.60	3.22	3.07	1.40	1.32	3.31	3.05	2.19	1.74	**5.33**	**4.31**	1.77	1.43	**4.59**	**4.12**
Columbus	1.61	1.63	3.25	3.06	1.41	1.33	3.30	3.06	2.21	1.73	**5.24**	**4.24**	1.73	1.44	**4.56**	**4.05**
Elkhart-Goshen	1.71	1.82	3.56	3.65	1.51	1.35	3.45	3.07	2.24	1.71	**5.13**	**4.27**	1.85	1.37	**4.62**	3.89
Evansville	1.61	1.55	3.16	3.05	1.41	1.26	3.25	2.98	2.08	1.65	**4.97**	**4.19**	1.74	1.38	**4.44**	**4.03**
Fort Wayne	1.69	1.73	3.48	3.43	1.50	1.35	3.42	3.07	2.25	1.72	**5.24**	**4.31**	1.83	1.38	**4.65**	3.98
Gary	1.77	1.83	3.63	3.68	1.50	1.32	3.45	3.03	2.14	1.73	**4.91**	**4.15**	1.87	1.42	**4.54**	3.97
Indianapolis	1.66	1.65	3.35	3.17	1.43	1.33	3.33	3.04	2.23	1.73	**5.27**	**4.26**	1.78	1.42	**4.59**	3.99
Kokomo	1.72	1.67	3.49	3.35	1.42	1.34	3.36	3.04	2.31	1.78	**5.24**	**4.31**	1.87	1.41	**4.69**	**4.05**
Lafayette	1.72	1.74	3.53	3.42	1.44	1.31	3.35	3.02	2.25	1.73	**5.12**	**4.22**	1.89	1.40	**4.63**	3.95
Louisville	1.61	1.65	3.21	3.12	1.41	1.32	3.29	3.03	2.18	1.70	**5.12**	**4.23**	1.75	1.42	**4.51**	3.96
Mich. Cty-L. P.	1.73	1.84	3.60	3.68	1.51	1.33	3.44	3.07	2.22	1.72	**5.06**	**4.20**	1.89	1.39	**4.61**	3.91
Muncie	1.67	1.68	3.43	3.27	1.42	1.34	3.35	3.08	2.25	1.72	**5.30**	**4.27**	1.81	1.40	**4.67**	**4.01**
South Bend-Mish.	1.71	1.82	3.56	3.65	1.52	1.35	3.46	3.07	2.24	1.71	**5.14**	**4.26**	1.86	1.37	**4.60**	3.88
Terre Haute	1.69	1.61	3.37	3.09	1.43	1.28	3.30	2.94	2.12	1.69	**5.03**	**4.20**	1.80	1.37	**4.54**	3.93
Average	1.68	1.70	3.41	3.32	1.45	1.32	3.36	3.04	2.21	1.72	**5.16**	**4.25**	1.81	1.40	**4.59**	3.99

Table 4
Temperature changes in ◦C from 2015 to 2080 under the two scenarios considered for all cities Studied. Average increases in high (h) and low (l) temperatures for each 3-month period are shown. The northernmost cities are shaded. Temperature increases higher than 4 ◦C are shown in bold.

The largest temperature increase forecast in this model was for the Jun–Jul–Aug period in RCP 8.5, which shows more than a 5◦ increase for the cities. Cities with projected maximum temperature increases above 6◦ (all > 6 ◦C increases were seen in the month of August) are Cincinnati, Columbus, FortWayne, Indianapolis, Kokomo, andMuncie. In both scenarios pronouncedly larger increases in temperature are seen in summer months by 2080, as compared with winter and transition seasons.

RCP 4.5 temperature increases forecast for the cities were less than 2 ◦C except in the Jun–Aug time period. RCP 8.5, on the other hand, shows temperature increases over 3 ◦C in all the time periods. August heat increases are more pronounced in the more southern or central parts of the state (highest in Indianapolis), but for other months the 4 northernmost cities generally see the highest temperature increases, with increases at or above the median and average in all months except April, where Gary is just below these markers.

For the modeling work, temperature data was needed to calculate HDD and CDD. We first calculated the average monthly temperatures (*t*avg) from *t*max and *t*min. Then, HDD was calculated using Eq. 5 around a base temperature of 18 ◦C.

$$\mathrm{HDD} = \sum_{n=1}^{12}(18 - T_{\mathrm{avg}})D_n \qquad (5)$$

whereD_n is the number of days in the month *n*.When the average temperature is higher than 18 for a given month, HDD = 0. The CDD calculation was done with the same equation, but the argument in the summation has the reverse signs.

Household size

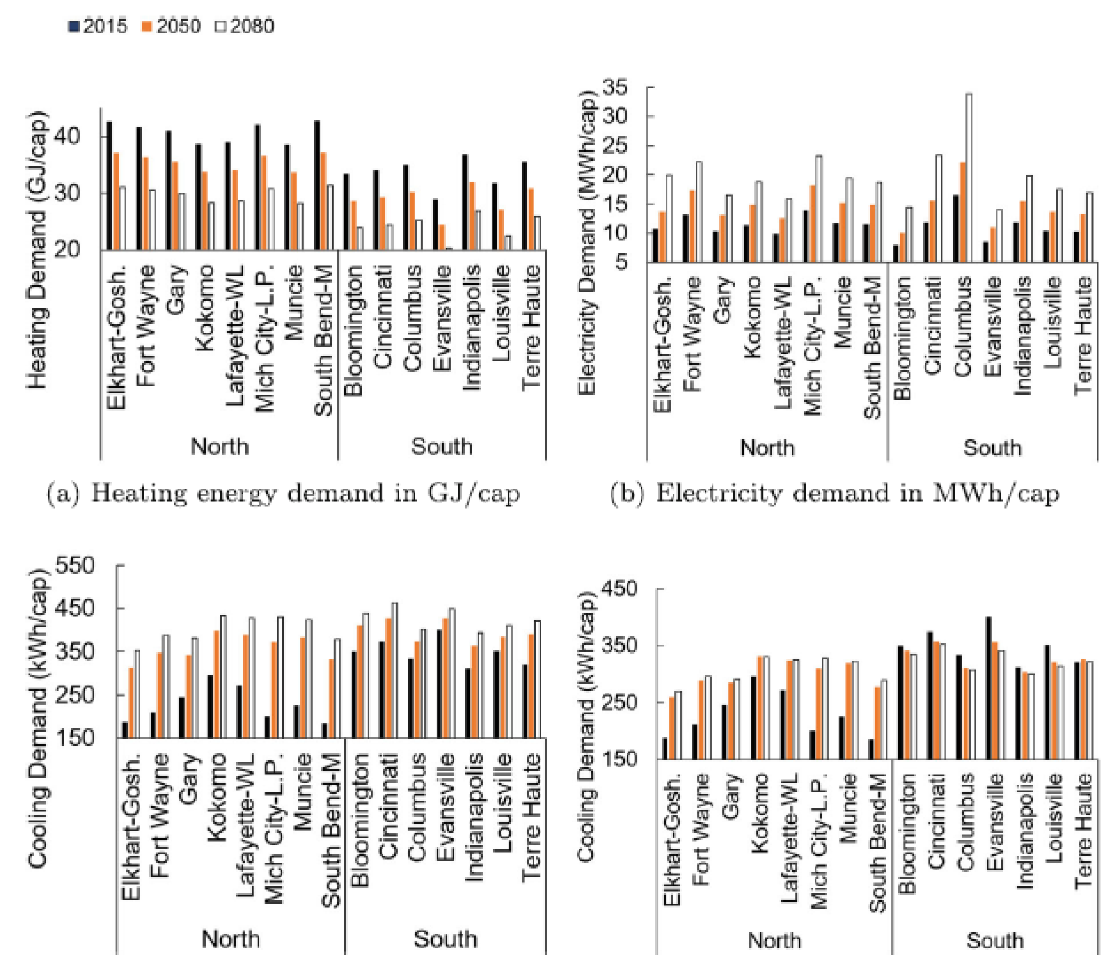
For cooling energy estimation, average household sizes were obtained for each city from the US Census Bureau's QuickFacts database (US Census Bureau 2017). Since the rate of change in household size has been very small and includes fluctuations, it was assumed constant for 2050 and 2080.

Gross domestic product

The US Census Bureau provides estimates of GDP per capita on a city level. They were assumed to rise 1% per year. Since GDP by household was needed, the GDP per capita values were multiplied by household size.

4 Results and discussion

Per capita energy demand projections Figure 1 shows per capita heating and electricity projections for the cities studied using the S-K method as well as cooling per capita both with and without efficiency gains in cooling equipments. Per capita heating demand is expected to fall in Indiana's cities by 7.8–13.3% by 2050 and 12.9–27.4% by 2080 (bounds correspond to the RCP 4.5 and 8.5 scenarios respectively). The spatial variation among cities for per capita heating demand declines over time as both scenarios project a more similar climate among IN cities over time. Modeled electricity demand is much less dependent on climatic shifts as the primary driver of electricity use as predicted by our model is decreasing inverse density due to urban sprawl. Per capita electricity usage is projected to increase over time by quite a bit—29.8–30.98% average increases are expected by 2050 and 64.38–67.56% increases are expected by 2080. Still the tight bounds on these estimates are due to the low impact of climate. The higher electricity costs for RCP 4.5, which has cooler temperatures than RCP 8.5, are due to electric heating's inclusion in the S-K model dataset, that is, all electricity end uses are accounted for and in the cities modeled electric heating will be larger than air conditioning. In part to overcome that limitation, we looked more closely at the end use of space cooling.



(a) Heating energy demand in GJ/cap (b) Electricity demand in MWh/cap

(c) Cooling demand with no efficiency improvement (d) Cooling demand with efficiency gains

Fig. 1 Per capita urban residential and commercial heating and electricity projections using the revised SK model for each city are shown in **a** and **b** for the RCP 8.5 scenario. The distinction between north and south is with respect to 40◦ latitude. Heating demand falls steadily in all cities whereas electricity demand rises. Urban residential per capita cooling estimates are shown in **c** and **d** with and without efficiency gains. Most cooling demand changes occur by 2050 with smaller changes through 2080. When efficiency gains are included in some cases, particularly in the southern cities, cooling demand falls from 2015 to 2080. Full data for figures as well as for the RCP 4.5 scenario is available in the SI, Tables 3–6.

In the case of cooling, we evaluated two cases. In one case we held the efficiency of cooling equipment constant for future scenarios, whereas in the second case we assumed improvements in efficiency. In Evansville, the urban area that currently has the highest projected per capita cooling energy use, as well as Bloomington, Cincinnati, Columbus, Indianapolis, and Louisville, the per capita use falls in both time periods in the high efficiency (HE) case. Other cities show an increase, most notably in the northern half of the state. Michigan City-La Porte shows the most dramatic increases, between 25–54% higher in 2050 and 51–63% higher in 2080 in the HE cases. With no efficiency improvements both Michigan City and South Bend would see over 100% increases in per capita cooling by 2080 in both the RCP 8.5 scenario.

Most striking is the falling standard deviation in cooling energy use, from 29 to 61% lower across all scenarios in 2050, and from 54 to 69% lower by 2080, showing that the overall profile for Indiana would be more homogeneous in terms of cooling needs under climate change. Accordingly, the penetration of air conditioners averaged 74.2% in our modeled estimates for 2015, but rises to over 90% in all cities by 2080 in the RCP 8.5 scenario. This is supported by Hamlet et al. (2019; this issue), who predict an increase in the number of "hot days," days with a high temperature of over 35 ◦C, across all Indiana urban areas included in their analysis, from historical numbers of 2.5–10.5 to a range of 58.6–98.2 days in the RCP 8.5 scenario. Full results by city are shown in Tables 5 and 6 in the supplementary information. The results indicate changing spatial patterns of energy demand in the state which will have implications on the grid load and also cost of energy specifically for cooling demand.

If the urban residential cooling demand competes with industrial demand (in some parts of Indiana, manufacturing industries such as corn-ethanol manufacturers are the major consumers of electricity in cooling towers), a major economic pricing issue may emerge, forming both a social and economic challenge. Hence, it is necessary to have better and accurate understanding of spatial changes in the energy demand due to climate change.

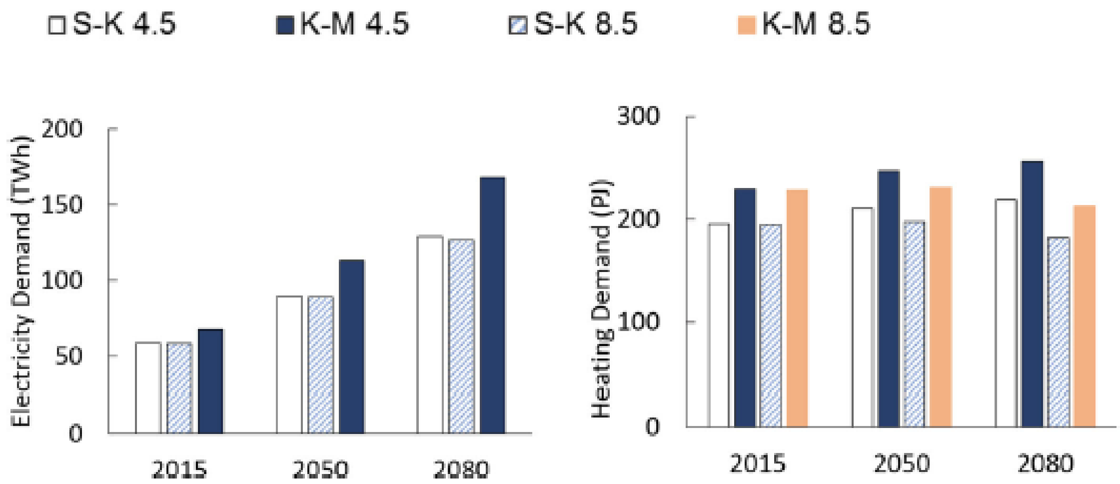
Total energy demand projections

If population growth is included we forecast an increase of energy use for space cooling in the residential sector for urban areas of Indiana. Heating demand, however, would increase in RCP 4.5 over time and in RCP 8.5 would actually decline as the climate effect overwhelms the effects of population growth, as shown in Fig. 2. Our population predictions are more uncertain for 2080, however. For overall electricity demand, which increases in both scenarios, inverse density and population growth dominate the climate effects. Cooling demand increases vary spatially, as shown in Fig. 3. Here it is also clear that most of the increased cooling demand in both scenarios comes by 2050.

Indianapolis is already a key driver of urban energy demand in Indiana currently accounting for 41% of Indiana's urban electricity use, 38% of urban heating, and 42% of urban transportation energy demand, according to our model. The population and growth trends anticipated over the course of the studied timespan are expected to intensify this, with Indianapolis driving 48% of Indiana's urban energy demand by 2080. Indianapolis' portion of total cooling can also be clearly seen in Fig. 3, where it dominates the contributions. Indianapolis's increased cooling demand represents between 44–56% of the total increases in the higher efficiency scenario and 43–50% of the increases in the same efficiency scenario. As the heating needs shrink and urban density declines, transportation is expected to represent an increasing share of the total energy use. Figure 4 shows this change over the time periods studied from the S-K model results. The K-M model shows the same trend, with transport rising from 38% of modeled energy use in 2015 to 46–47% in 2080.

4.1 Limitations and model robustness

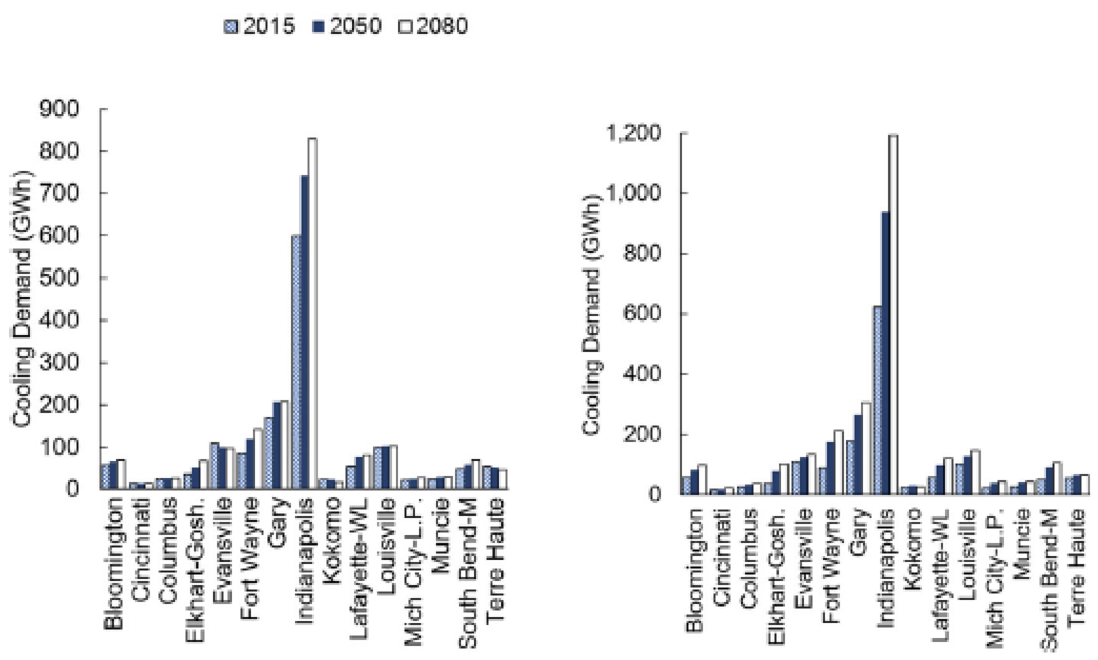
One of the major limitation of urban energy demand projections is the lack of data at this level of fine resolution. While most data on energy consumption are aggregated at state demand projection responsive to changing factors such as climate change, economic prosperity, and demographics will need to be made at finer scale such as urban scale or national scale, energy consumption is centered in urban areas. Hence, a better energy demand projection responsive to changing factors such as climate change, economic prosperity, and demographics will need to be made at finer scale such as urban scale. The existing S-K and K-M models were made possible by projects that supported data collection at such a fine scale and both these studies have cautioned about the use of these models for non-representative cities. Most statistical models run into the issue of extrapolation if the models are used for projections beyond the underlying modeling data. The models used here were based on a global set of cities with a generally higher population density. To address this limitation and ensure the applicability of the S-K model to Indiana cities a hidden extrapolation test was run as used by Singh and Kennedy (2015) and also described in Douglas and Runger (2010). This test defines the minimal convex area containing all regressor data points and determines whether the model results fall inside the area, since if they are outside extrapolation takes place. In the future, fine-scale data on urban energy demand would help improve the applicability of the S-K model, since regressions could be run with regional specificity. Still, according to the extrapolation test, for 2050 over 90% of the cities modeled are within the reasonable bounds of the S-K model. As time goes on our uncertainty about the parameters increases as does the amount of extrapolation present in our model. All extrapolation test results are provided in the SI, section 3, Tables 7–10.



(a) Urban electricity demand in Twh

(b) Urban heating demand in PJ

Fig. 2 Total electricity and heating demand are shown as modeled by the two techniques. Electricity shows consistent growth in both models, while heating demand falls in the RCP 8.5 scenario, even accounting for population growth. Note that in the K-M model there is no difference between the electricity projections based on temperature, so RCP 8.5 and 4.5 give the same results. Growth for electricity demand is also very similar between the two scenarios in the S-K model



(a) Total urban residential cooling RCP 4.5, efficiency gains

(b) Total urban residential cooling RCP 8.5, no efficiency gains

Fig. 3 Projections for total cooling demand (GWh) by city are shown for the RCP 4.5 scenario, including the efficiency improvement assumption (so the most conservative estimate) are shown on the left, to contrast with the most aggressive estimate given by RCP 8.5 with no efficiency gains, shown at right. The sequence and shading denote the years in the study. When population is taken into account, most increases are still primarily seen from 2015 to 2050, with flatter increases from 2050 to 2080, and absolute decreases for Evansville, Kokomo and Terre Haute in the conservative scenario. Indianapolis dominates the total demand here due to its large population

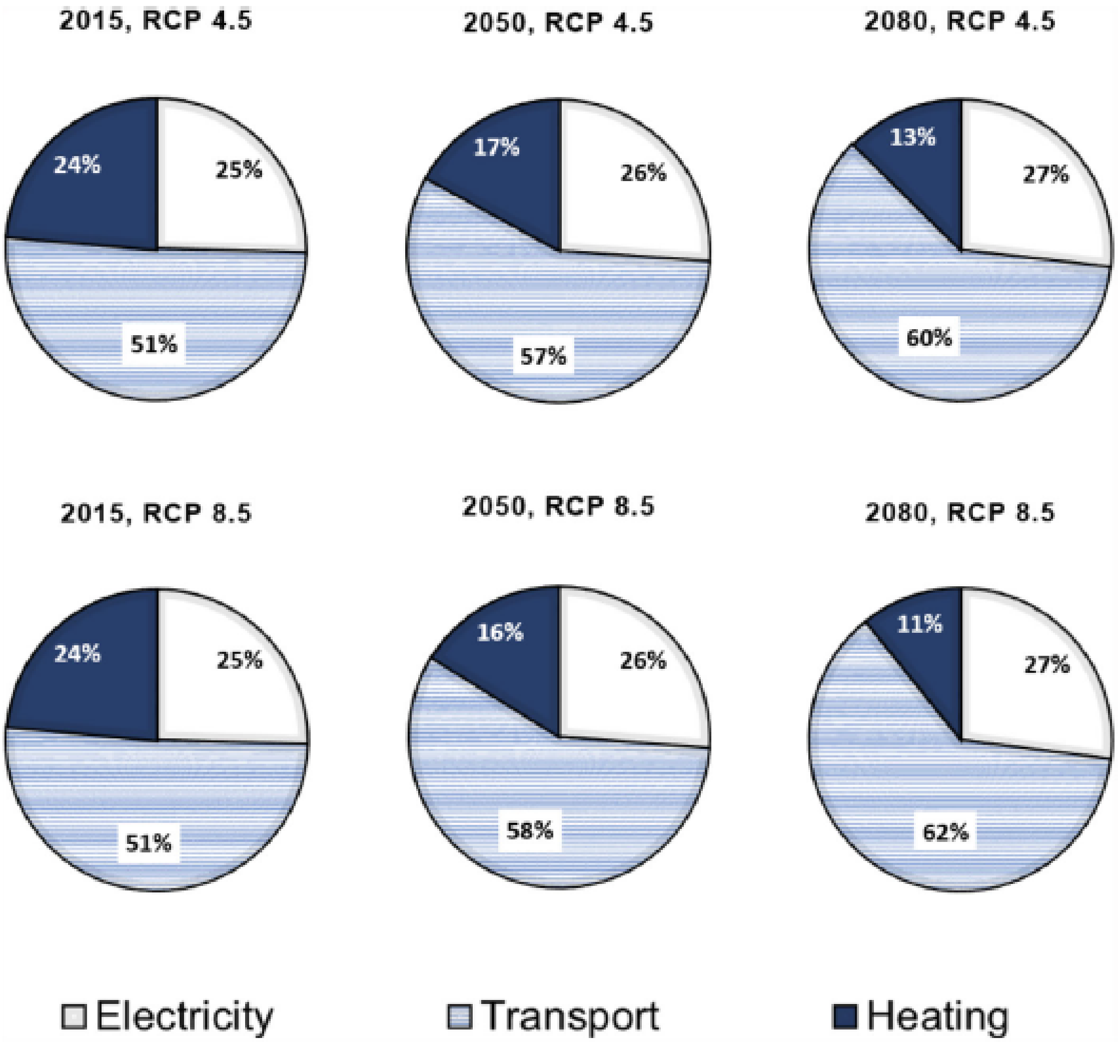


Fig. 4 Changing energy use categories over time forecast using the S-K model. Forecasts are for residential and commercial energy demand. Electricity should include cooling, but the projections for cooling are from a different methodology so are not indicated here. Also, since cooling projections are only for residential, they will represent a small portion of the total electricity demand shown here

HDD and CDD are calculated from average monthly temperatures. This technique provides underestimates relative to calculations using daily temperatures, since the daily variation is lost. Peaks in temperature are lost, as are any effects of consecutive days at high or low temperature. Results from Singh and Kennedy (2015) showed that monthly calculations still represent the trends adequately, although finer temporal resolution would improve accuracy.

Cooling energy use is strongly affected by the efficiency of space cooling equipment. In the calculations initially done as reported in Raymond et al. (2019; this issue) our baseline data for 2015 was calculated using an efficiency value of 3.81; hence, the trend lines shown here differ in terms of magnitude in the no efficiency improvement scenario, and in terms of relative increase in the high efficiency scenario. For 2050 and 2080 projections we relied on estimates of technological improvements from Rong et al. (2007), but this may be conservative. The high efficiency scenario from GCAM (Iyer et al. 2017) includes an efficiency factor of 7.03 for 2050, much higher than the factor of 4.02 used in our model. Using this factor for 2050 and 2080 would show decreased cooling demand in all years and scenarios, ranging from a 14% average decrease in 2080 for RCP 8.5 to a decrease of 32% in 2050 for RCP 4.5. Again there is spatial variability, with the highest increase (26%) shown in Elkhart-Goshen, one of the northernmost cities with a very moderate climate currently, with a corresponding decrease of 49% in Kokomo, which for 2015 shows a higher penetration of air conditioning than more northern cities (RCP 8.5 scenario, 2080).

5 Conclusions

Urbanization drives energy demand patterns throughout the world, hence most countries are now focusing on future strategies based on urban demand changes. Climate change impacts will differ in urban areas within the same region, however, due to their specific climatic conditions. Hence, coupling the results from downscaled climate change models with urban energy demand models is necessary to provide reliable information about impact of climate change at fine scale. This will improve the strategies for addressing climate change impacts.

This work is an initial attempt to understand the spatial changes in energy demand in Indiana's urban regions and to quantify the demand changes in response to long-term projections related to climate change. The underlying temperature changes show higher maximum and minimum temperatures, with the summer maxima outpacing other increases. Warmer winters will be seen, with more of the change in winter happening in the northernmost parts of the state. Indiana's winter climate loses some of its spatial variability in cities as the state as a whole becomes much warmer (see also table S1 in Hamlet et al. 2019; this issue). As described in Section 4.1, the projected heating or cooling demand may be lower than seen elsewhere since the CDD and HDD estimated are reduced when an average monthly temperature is used rather than calculated with higher temporal resolution. Yet in previous work HDD estimated this way has been shown to adequately demonstrate the trend. In the case of cooling, we still show all cities using the maximum cooling energy per capita by the end of the study period.

In terms of energy demand, this means a lower heating but a higher cooling bill. While we do expect an overall decline in energy costs due to climate change for the residential sector, a general projection for the commercial sector was not done. If we consider data from the most recent CBECS report (US Energy Information Administration 2012) together with our classification of cities in terms of HDD and CDD by proxy using 2014 real temperatures, Indiana's cities move from the category of 11% of electricity in the commercial sector devoted to cooling to the category of 20–27% of electricity devoted to cooling. Nateghi and Mukherjee (2017) estimated an increase in cooling energy demand for the commercial sector of 5.1–5.4% during the same model period. So while we were not able to model the urban portion of the commercial cooling, it is likely to increase.

A recent study that performed a detailed simulation of energy use by buildings in the eastern region of the USA found similar results in terms of overall energy use—lower heating loads and increased cooling energy use in buildings (Dirks et al. 2015). They also found, however, that the additional cooling load would result in additional generation capacity needs, particularly in Minnesota, where a projected 23% increase in cooling would result in more than 100% of increased electricity capacity generation. We have not studied this issue since we modeled energy demand totals, but spatial trends here may indicate the need for closer study. By the end of the study period we forecast a per capita cooling load in northern Indiana cities comparable to current cooling loads in southern Indiana cities except in the highest efficiency scenario, which may have ramifications for generation capacity in these areas. In fact, most of the increase happens by 2050, so within the planning horizon.

The S-K model results show that based on current usage trends, transportation takes up an increasing portion of the energy usage over time. But this has to be put in context in terms of other large scale changes that may occur, such as electrification of transport. Currently electric vehicles make up a small portion of the fleet, but signs point to a potentially precipitous increase. A recent study Arbib and Seba (2017) looks at the potential for electric vehicles and the autonomous technology to change the business model for transportation, causing a rapid shift from the car ownership model to a transportation services model. Such a shift would allow electric vehicles to act as storage capacity for renewables.

This study shows that much of Indiana's energy needs will come in urban centers, particularly Indianapolis. Transportation will become increasingly important as heating needs diminish and cooling needs are expected to increase. Improvements in efficiency may modulate demand increases from cooling.

More data on urban energy demand and usage would be helpful in order to develop modeling tools with higher spatial resolution. Further, improving the demand change model to include urban heat island effects would further improve the accuracy of demand projections. Commercial cooling models are limited as well.

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